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Takahashi

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(54) **SENSOR OUTPUT CHANGE DETECTION**

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***G06F 17/18*** (2006.01)
(Continued)

(52) **U.S. Cl.**
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See application file for complete search history.

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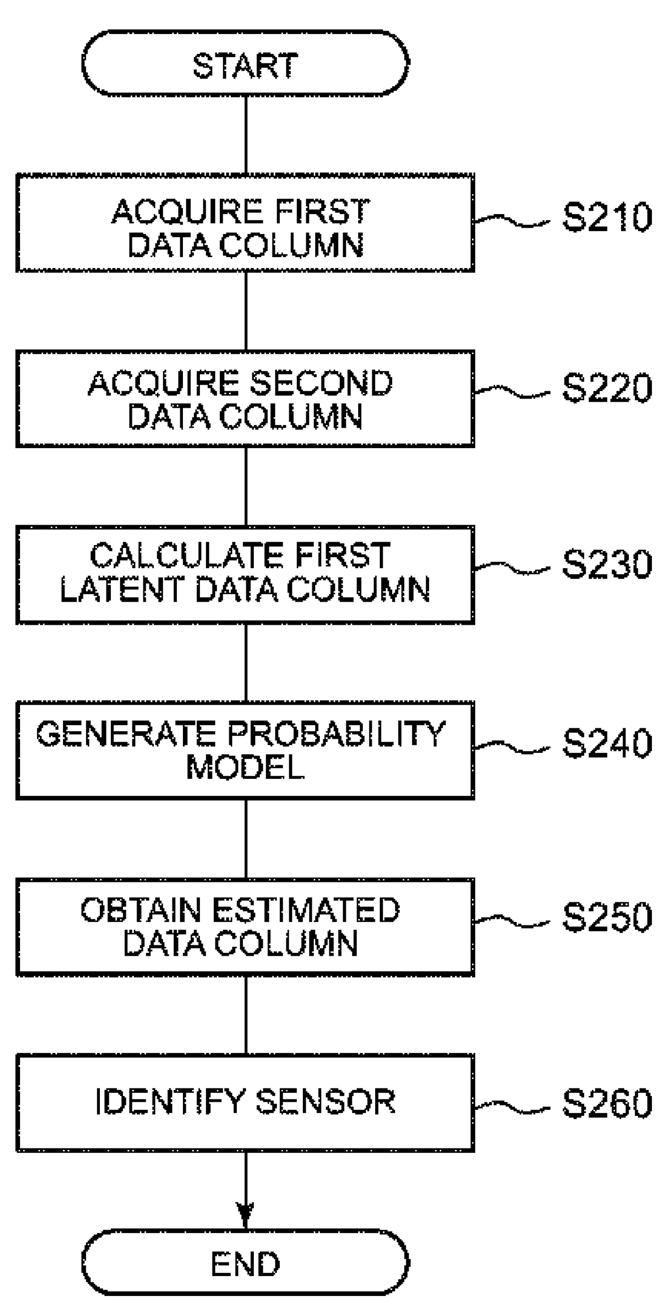
(57) **ABSTRACT**

A method includes acquiring a first data column output from a plurality of sensors, generating a model for estimating data from the plurality of sensors on the basis of the first data column, acquiring a second data column output from the plurality of sensors, obtaining an estimated data column corresponding to the second data column based on the model by using regularization for making an error between the second data column and the estimated data column sparse, and identifying a sensor in which a change occurred between the first data column and the second data column on the basis of the error between the second data column and the estimated data column. A corresponding computer program product and apparatus are also disclosed herein.

**20 Claims, 8 Drawing Sheets**



(51) **Int. Cl.**

| | |
|---|---|
| ***G06F 16/22*** | (2019.01) |
| ***G06F 16/23*** | (2019.01) |
| ***G06K 9/00*** | (2006.01) |
| ***G06K 9/62*** | (2006.01) |

(52) **U.S. Cl.**

CPC ......... ***G06F 17/18*** (2013.01); ***G06K 9/00496*** (2013.01); ***G06K 9/6243*** (2013.01); *G06K 2009/00583* (2013.01)

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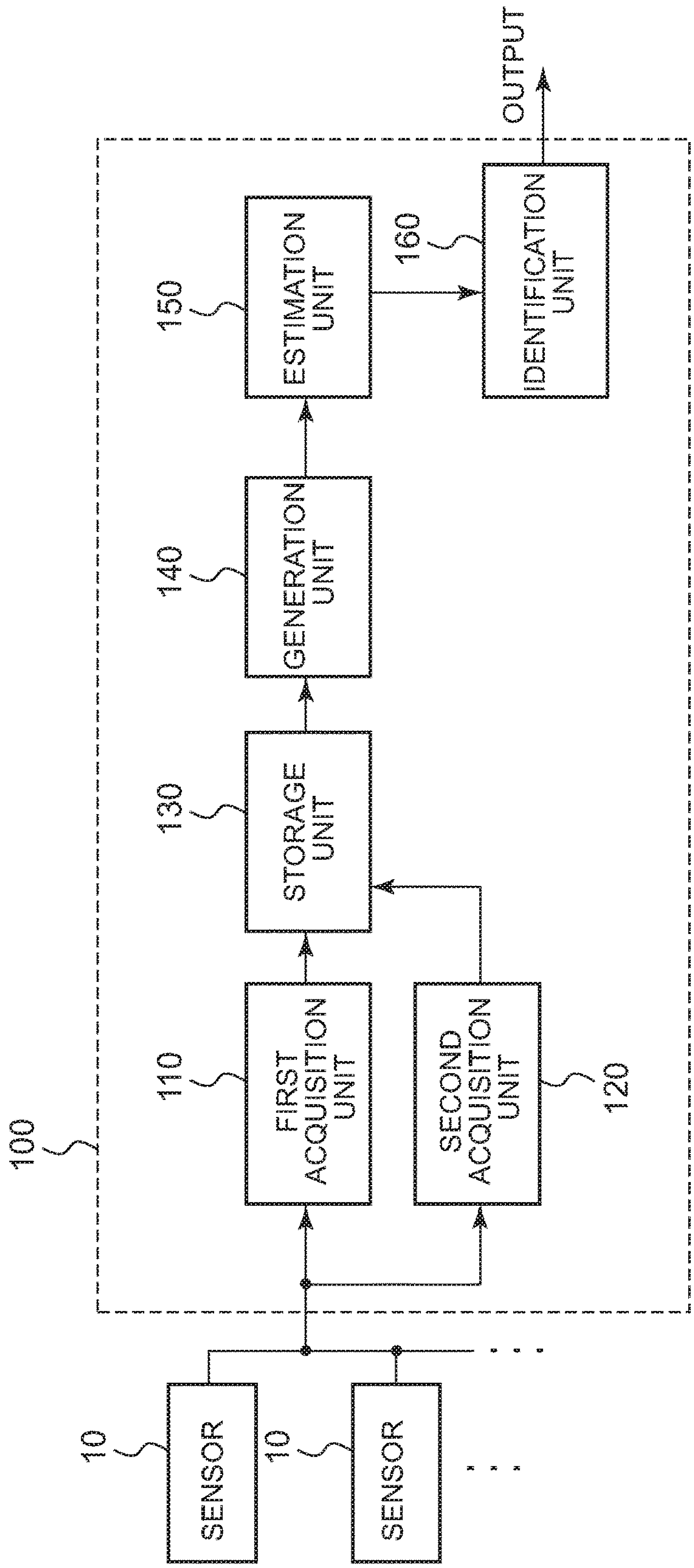

SENSOR
SENSOR
10
10
100
FIRST ACQUISITION UNIT
110
SECOND ACQUISITION UNIT
120
STORAGE UNIT
130
GENERATION UNIT
140
ESTIMATION UNIT
150
IDENTIFICATION UNIT
160
OUTPUT

FIG. 1A

$$\underset{X}{\operatorname{argmin}}\ \operatorname{tr}(XLX^T) \text{ subject to } XDX^T = 1,\ X D\vec{1} = \vec{0}$$
$$X \equiv (\vec{x}_1, \ldots, \vec{x}_N) \in \vec{R}^{Q \times N}$$

FIG. 1B

$$L \equiv D - W$$
$$w_{n,m} \equiv \exp\left((-1/\sigma^2)\|\vec{y}_n - \vec{y}_m\|^2\right)$$
$$D \equiv \operatorname{diag}\left(\left\{\sum_m w_{n,m}\right\}_{n=1}^{N}\right)$$

FIG. 1C

$$p(\vec{\chi}_m, \vec{v}_m | \vec{\eta}_m, \vec{y}_n) = (\Sigma_n w_{n*}/2\pi)^{1/2} \exp[((-1/2)\sum_n w_{n*})\ \|\vec{x}_n - \vec{\chi}_m\|^2]$$
$$\times (\Sigma_n k_{n*}/2\pi)^{1/2} \exp[((-1/2)\sum_n k_{n*})\ \|\vec{y}_n - \vec{v}_m\|^2]$$

$$w_{n*} \equiv \exp((-1/\sigma_y^2)\|\vec{y}_n - \vec{n}_m\|^2)$$
$$k_{n*} \equiv \exp((-1/\sigma_y^2)\|\vec{x}_n - \vec{\chi}_m\|^2)$$

FIG. 1D

$$(\{\vec{\chi}_m{}'\},\{\vec{v}_m{}'\}) = \underset{\vec{\chi}_m,\ \vec{v}_m}{argmin}[-\sum_m \log p\ (\vec{\chi}_m,\ \vec{v}_m|\vec{\eta}_m,\ \vec{y}_n) \\ -\log p\ (\vec{v}_1,\ldots,\ \vec{v}_M|\vec{\eta}_1,\ldots,\ \vec{\eta}_M)]$$

FIG. 1E

$$-\log p\ (\vec{v}_1,\ldots,\ \vec{v}_M|\vec{\eta}_1,\ldots,\ \vec{\eta}_M) = \lambda_1\sum_d\sqrt{\sum_m||v_{md} - h_{md}||^2} \\ + \lambda_2\sum_m||\vec{v}_m - \vec{v}_{m-1}||_{1,1}$$

FIG. 1F

$$S_{n,d}=|\eta_{md} - v_{nd}'|$$

FIG. 1G

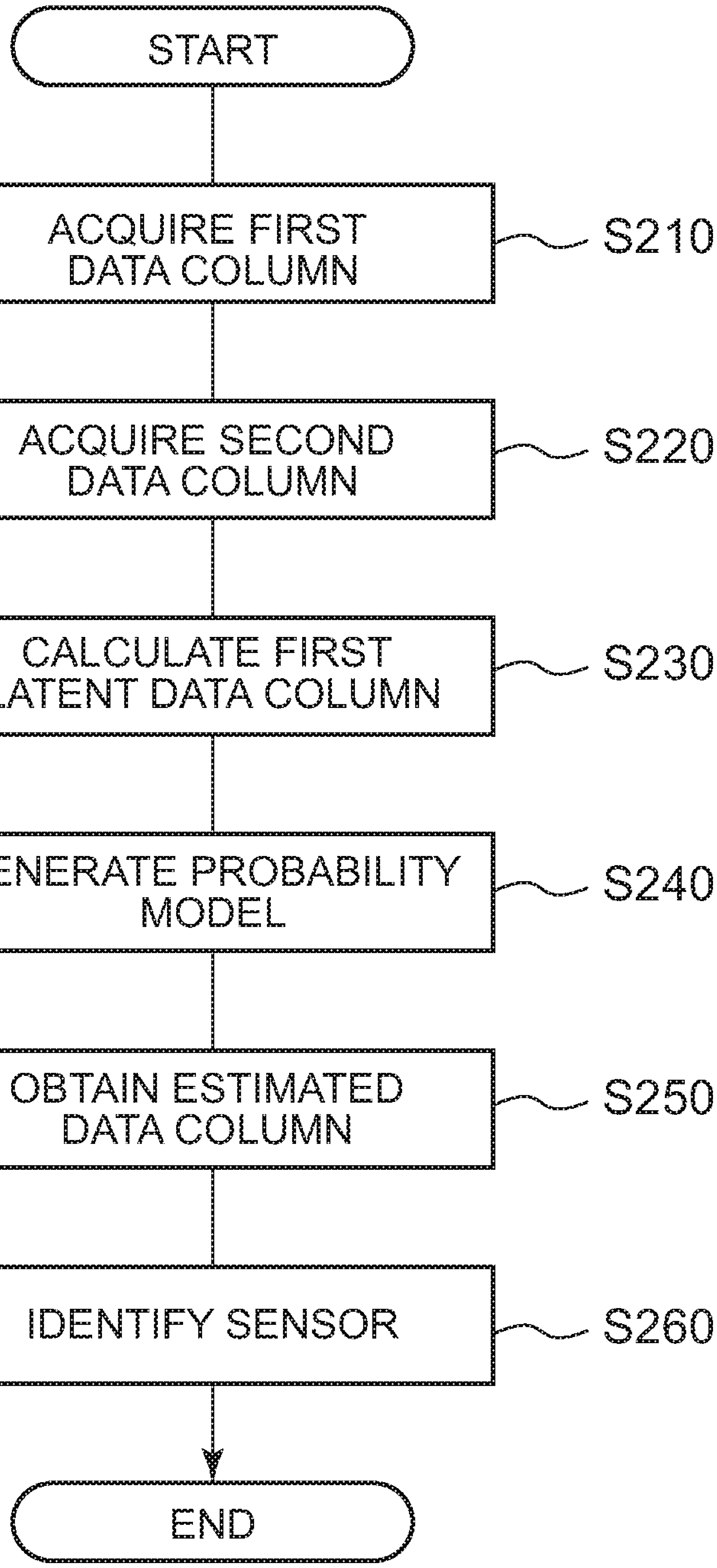

START
ACQUIRE FIRST DATA COLUMN
S210
ACQUIRE SECOND DATA COLUMN
S220
CALCULATE FIRST LATENT DATA COLUMN
S230
GENERATE PROBABILITY MODEL
S240
OBTAIN ESTIMATED DATA COLUMN
S250
IDENTIFY SENSOR
S260
END

FIG. 2

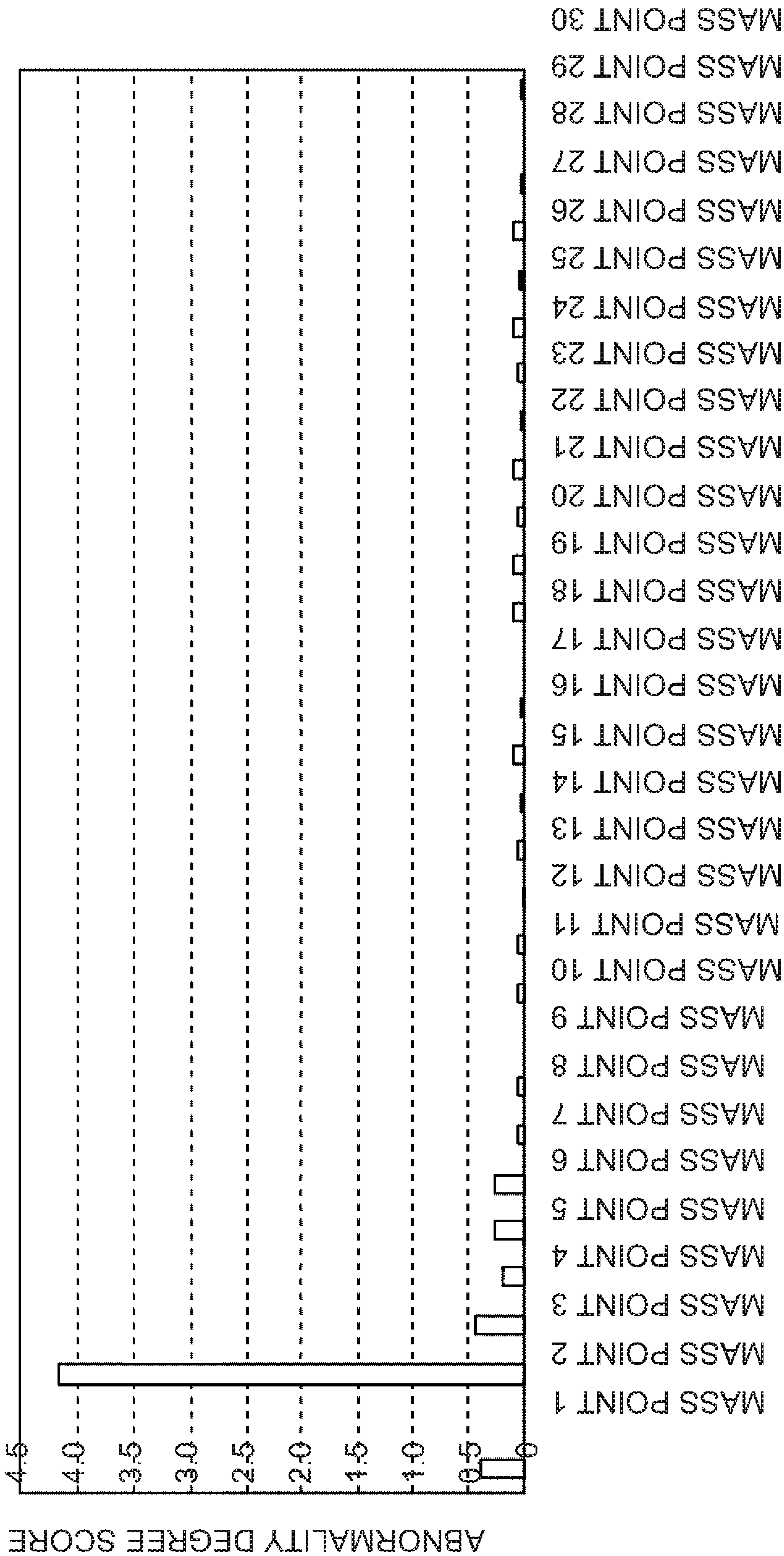
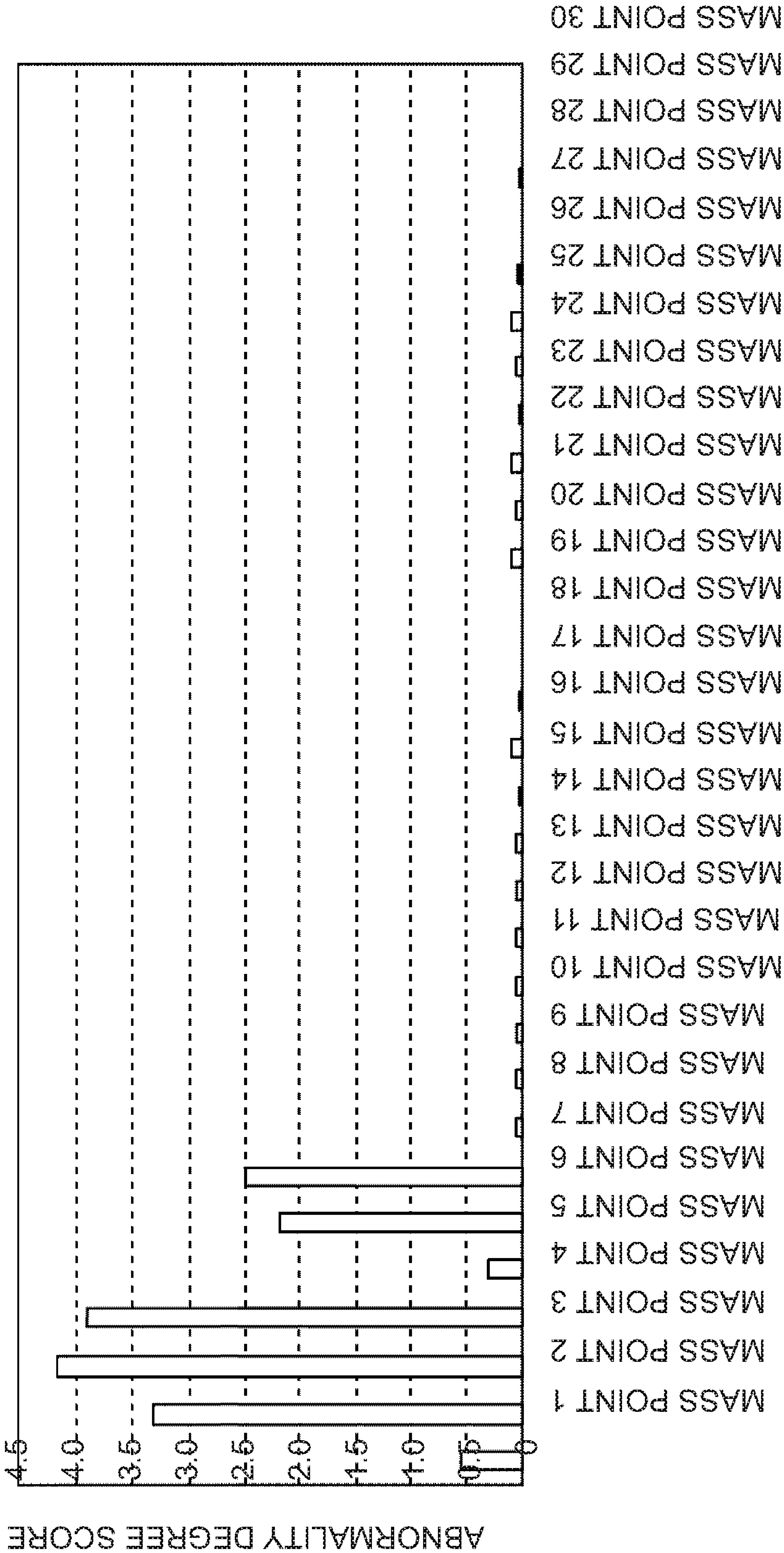

ABNORMALITY DEGREE SCORE
0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
MASS POINT 1
MASS POINT 2
MASS POINT 3
MASS POINT 4
MASS POINT 5
MASS POINT 6
MASS POINT 7
MASS POINT 8
MASS POINT 9
MASS POINT 10
MASS POINT 11
MASS POINT 12
MASS POINT 13
MASS POINT 14
MASS POINT 15
MASS POINT 16
MASS POINT 17
MASS POINT 18
MASS POINT 19
MASS POINT 20
MASS POINT 21
MASS POINT 22
MASS POINT 23
MASS POINT 24
MASS POINT 25
MASS POINT 26
MASS POINT 27
MASS POINT 28
MASS POINT 29
MASS POINT 30

FIG. 3


MASS POINT 1
MASS POINT 2
MASS POINT 3
MASS POINT 4
MASS POINT 5
MASS POINT 6
MASS POINT 7
MASS POINT 8
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MASS POINT 10
MASS POINT 11
MASS POINT 12
MASS POINT 13
MASS POINT 14
MASS POINT 15
MASS POINT 16
MASS POINT 17
MASS POINT 18
MASS POINT 19
MASS POINT 20
MASS POINT 21
MASS POINT 22
MASS POINT 23
MASS POINT 24
MASS POINT 25
MASS POINT 26
MASS POINT 27
MASS POINT 28
MASS POINT 29
MASS POINT 30
0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
ABNORMALITY DEGREE SCORE

FIG. 4

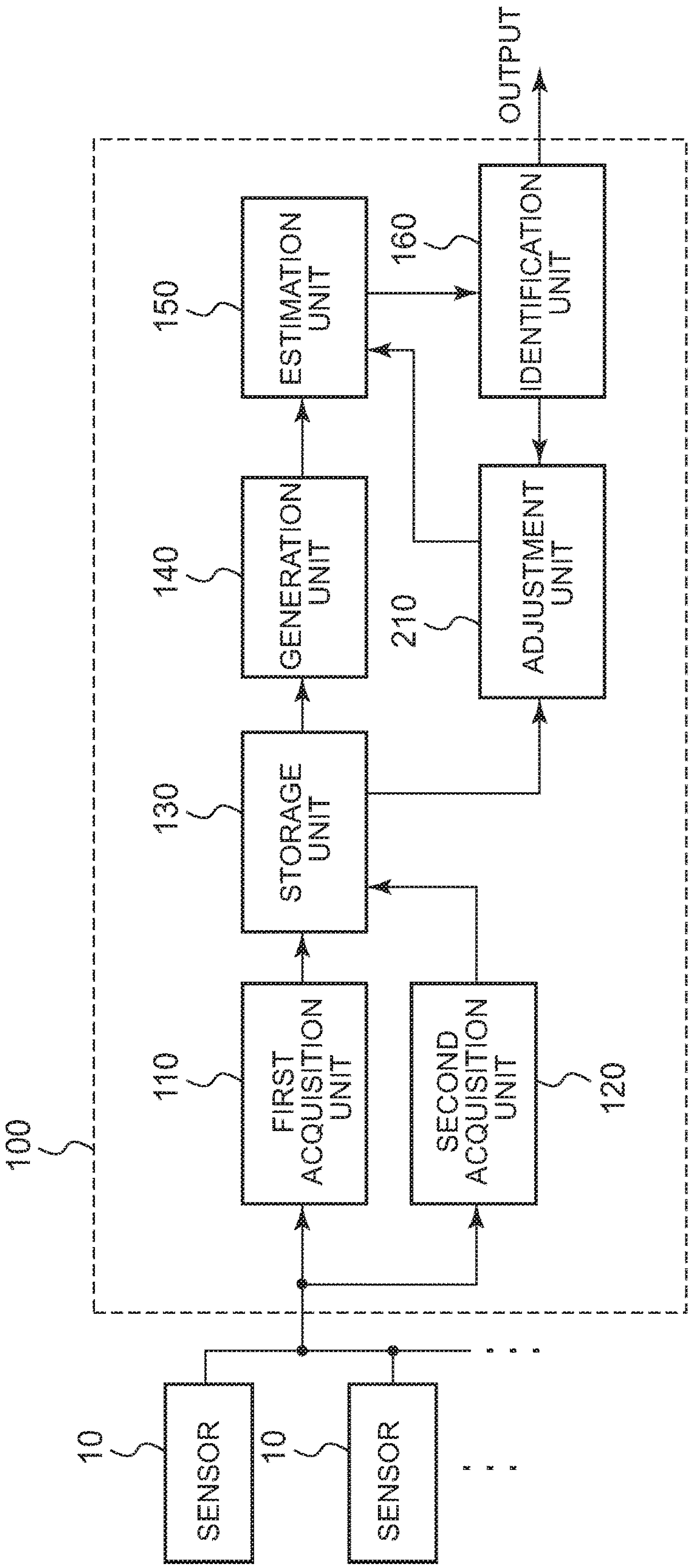
100
10
SENSOR
10
SENSOR
110
FIRST ACQUISITION UNIT
120
SECOND ACQUISITION UNIT
130
STORAGE UNIT
140
GENERATION UNIT
150
ESTIMATION UNIT
160
IDENTIFICATION UNIT
210
ADJUSTMENT UNIT
OUTPUT

FIG. 5

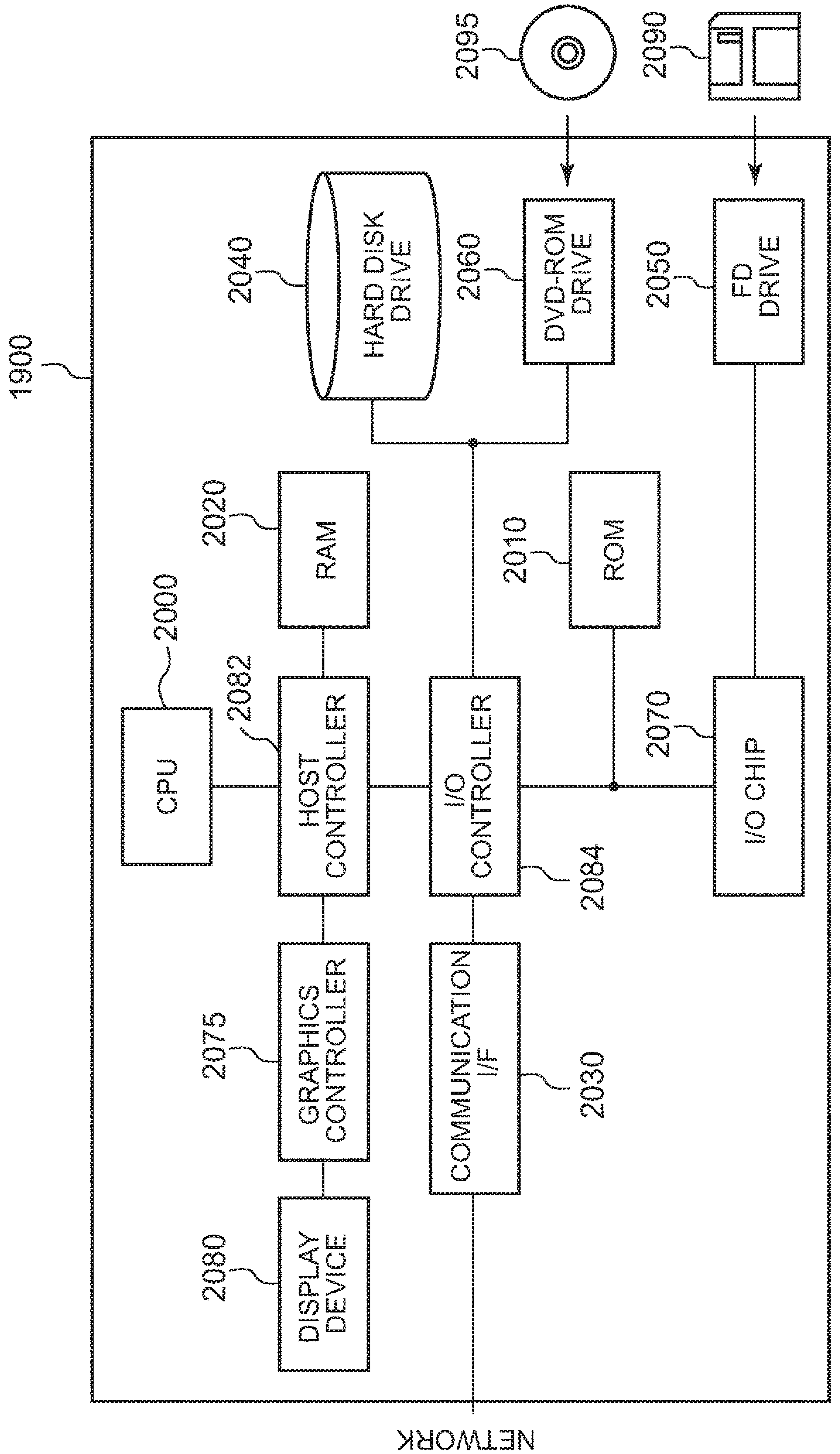
1900
2095
2090
2040
HARD DISK DRIVE
2060
DVD-ROM DRIVE
2050
FD DRIVE
2020
RAM
2010
ROM
2000
CPU
2082
HOST CONTROLLER
I/O CONTROLLER
2084
2070
I/O CHIP
2075
GRAPHICS CONTROLLER
COMMUNICATION I/F
2030
2080
DISPLAY DEVICE
NETWORK

FIG. 6

# SENSOR OUTPUT CHANGE DETECTION

## BACKGROUND OF THE INVENTION

The present invention relates generally to the field of data processing and more particularly to processing sensor data.

Sensors may be provided on a complicated system such as an automobile or a manufacturing device. Time series data acquired from the sensors may be analyzed. Particularly, time series data may be analyzed to monitor the presence or absence of abnormalities even in systems with hundreds of sensors.

## SUMMARY

An apparatus includes a first acquisition unit which acquires a first data column output from a plurality of sensors, a generation unit which generates a model for estimating data from the plurality of sensors on the basis of the first data column, a second acquisition unit which acquires a second data column output from the plurality of sensors, an estimation unit which obtains an estimated data column corresponding to the second data column based on the model by using regularization for making an error between the second data column and the estimated data column sparse, and an identification unit which identifies a sensor in which a change occurred between the first data column and the second data column on the basis of the error between the second data column and the estimated data column.

A method includes acquiring a first data column output from a plurality of sensors, generating a model for estimating data from the plurality of sensors on the basis of the first data column, acquiring a second data column output from the plurality of sensors, obtaining an estimated data column corresponding to the second data column based on the model by using regularization for making an error between the second data column and the estimated data column sparse, and identifying a sensor in which a change occurred between the first data column and the second data column on the basis of the error between the second data column and the estimated data column. A corresponding computer program product and apparatus are also disclosed herein.

The foregoing summary of the invention is not a list of features required for the present invention. In addition, any sub-combination of these features could also constitute the invention.

## BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1**A is a block diagram illustrating a configuration example of a detection device operably coupled to a plurality of sensors in accordance with at least one embodiment of the present invention;

FIGS. **1**B-**1**G are equation diagrams in accordance with at least one embodiment of the present invention;

FIG. **2** is a flowchart illustrating one embodiment of an operation flow in accordance with at least one embodiment of the detection device;

FIG. **3** is a diagram illustrating an example of a simulation result in accordance with at least one embodiment of the detection device;

FIG. **4** is a diagram illustrating an example of a simulation result obtained by an existing detection device which calculates the scores of abnormality degrees of a plurality of sensors;



FIG. **5** is a block diagram illustrating a variation of the detection device; and

FIG. **6** is a block diagram illustrating an example of the hardware configuration of a computer in accordance with at least one embodiment of the detection device.

## DETAILED DESCRIPTION

Hereinafter, the present invention will be described in various embodiments. It should be noted, however, that the following embodiments are not intended to limit the scope of the appended claims, and that not all the combinations of features described in the embodiments are necessarily required by the present invention.

The abnormality degrees of sensors may be scored for identification on the basis of the degree of change in the structure of a relation between the sensors with respect to a sensor group (normal sensors) which shows a detection result in which an input signal is within a normal signal range and a sensor group (abnormal sensors) which shows a detection result in which an input signal is within an abnormal signal range from a plurality of time series data. In the case where, for example, there are a hundred or more of sensors mutually having a complicated correlation in a physical system, however, it is difficult to pick up only abnormal sensors and sensors having a strong correlation with an abnormal sensor also have high scores of abnormality in some cases.

FIG. **1**A illustrates a configuration example of a detection device **100** according to an embodiment along with a plurality of sensors **10**. The plurality of sensors **10** may be mounted on an object such as an automobile, a ship, an aircraft, or other transport machinery, a manufacturing device, or a monitoring device and transmit detection results to the detection device **100**. The sensor **10** may be connected to the detection device **100** by wired communication or alternatively may be connected to the detection device **100** by wireless communication. This embodiment will be described by giving an example in which the object is an automobile.

The sensor **10** may be, for example, a temperature sensor for engine cooling water, a temperature sensor for engine intake air, an oil temperature sensor, an intake pipe internal pressure sensor for a fuel injection device, a supercharging pressure sensor for a turbocharger, a throttle position sensor, a steering angle sensor, a vehicle height sensor, a liquid level sensor, a rotation speed sensor, a knock sensor, an acceleration sensor, an angular velocity sensor, a geomagnetic sensor, a flow sensor, an oxygen sensor, a lean air-fuel ratio sensor, or the like. In some cases, several hundred to one thousand or more sensors **10** are provided at a time.

In this case, it is necessary to process several hundred to one thousand or more arrays of time series data. Regarding the time series data of the sensors provided on the automobile and the like, data values themselves and the structure of a relation between the sensors dynamically change and the dynamic change may abruptly occur and may not be foreseeable in advance. As an example, in the case where a car is "accelerated" by an action of "treading on an accelerator," the structure of a relation between the sensors is strengthened with respect to the outputs from the throttle position sensor, the rotation speed sensor, and the acceleration sensor. Specifically, the structure of the relation between the sensors dynamically changes at an unpredictable time (for example, regarding a user's operation, a situation of the automobile, or the like) and therefore the sensors may have a mutually-complicated correlation.

Moreover, in this case, a detected output at each sensor and a range of values for determining that the detected output is in the normal state vary according to the situation of the automobile such as passengers (a loading amount of baggage or the like), the current speed, the road gradient during traveling, whether the automobile is traveling on a straight road or on a curved road (in the case of a curved road, the degree of curvature), or the like. Specifically, an output of each sensor and criteria for judgment of whether the situation of the automobile is normal dynamically change at an unpredictable time (for example, regarding a user's operation, a situation of the automobile, or the like).

In this manner, even in the case of time-series signals from the same sensor, data values and the criteria for judgment significantly change in response to a change in the structure of a relation with other sensors and therefore it is difficult to perform meaningful processing even if data is compared with past data. In this case, it is conceivable to treat the sensors as multivariable systems for analysis. The calculation amount, however, increases in an exponential manner as the number of sensors increases. Therefore, this approach is distant when using several hundred to one thousand or more sensors.

Moreover, there can also be an idea of estimating the degree of change in the structure of the relation between the sensors and scoring the abnormality degrees of the sensors according to the estimation result. In this case, it is possible to discriminate a normal sensor from an abnormal sensor by comparing the scored abnormality degree with a predetermined threshold value or the like. When this type of discrimination method is used, however, not only the score of an abnormal sensor, but also the score of a normal sensor having a strong correlation with the abnormal sensor is also calculated as a great value enough to show abnormality in some cases, in the case of scoring the abnormality degrees of the sensors mutually having a complicated correlation.

Accordingly, the detection device **100** according to this embodiment is a detection device which detects a change in outputs from a plurality of sensors, wherein learning data is used to generate a model for mapping output data from the plurality of sensors **10** to a low-dimensional latent space and then reconstructing the output data in the original dimensions. Furthermore, in the case of using the model to map test data to a latent space and to reconstruct the test data in the original dimensions, the detection device **100** performs regularization so as to enlarge a change of data which behaves abnormally, thereby increasing the score of the abnormal sensor in comparison with the normal sensors. The detection device **100** includes a first acquisition unit **110**, a second acquisition unit **120**, a storage unit **130**, a generation unit **140**, an estimation unit **150**, and an identification unit **160**.

The first acquisition unit **110** acquires a first data column output from the plurality of sensors **10**. The first acquisition unit **110** acquires the first data column as learning data. Moreover, the first acquisition unit **110** may acquire a first data column stored in the detection device **100** or an external storage device. Furthermore, the first acquisition unit **110** may acquire a first data column supplied by an external device connected to the plurality of sensors **10**.

The first acquisition unit **110** preferably acquires outputs from the plurality of sensors **10** in a state where the outputs represent a normal behavior of the automobile which is a measuring object as a first data column for learning. Alternatively, the first acquisition unit **110** may acquire a supposed data column as the first data column from a prediction model for generating a data column supposed to be output from the plurality of sensors **10**, a model for a device to be measured, or the like.

This embodiment will be described by giving an example that the first acquisition unit **110** acquires a first data column corresponding to first outputs output in time series by the plurality of sensors **10** when the automobile, which is an object equipped with the plurality of sensors **10**, is in a normal state. The first acquisition unit **110** supplies the acquired first data column to the storage unit **130**.

The second acquisition unit **120** acquires a second data column output from the plurality of sensors **10**. The second acquisition unit **120** acquires the second data column as test data. Moreover, the second acquisition unit **120** may acquire a second data column stored in the detection device **100** or an external storage device. Furthermore, the second acquisition unit **120** may acquire a second data column supplied by an external device connected to the plurality of sensors **10**.

The second acquisition unit **120** acquires a second data column detected from the automobile which is a measuring object. For example, the second acquisition unit **120** acquires outputs in a predetermined period, which is different from the period in which the first acquisition unit **110** acquires the first data column, as a second data column.

In this case, the second acquisition unit **120** preferably acquires data, which is output in time series from the plurality of sensors **10**, as a second data column in the case where the automobile is operating. This embodiment will be described by giving an example that the second acquisition unit **120** acquires a second data column corresponding to second outputs output in time series from the plurality of sensors **10** in the case where the automobile equipped with the plurality of sensors **10** is in the operating state. The second acquisition unit **120** may supply the acquired second data column to the storage unit **130**.

The storage unit **130**, which is connected to the first acquisition unit **110** and to the second acquisition unit **120**, stores the first data column and the second data column which have been received. Moreover, the storage unit **130** may store data generated by the detection device **100** and intermediate data processed in the course of generating the data or the like. Furthermore, the storage unit **130** may supply stored data to a requestor in response to a request from each unit in the detection device **100**.

The generation unit **140**, which is connected to the storage unit **130**, generates a model for estimating data from the plurality of sensors **10** on the basis of the first data column. The generation unit **140** generates a model known as a latent variable model, as a probability model which represents the operation of the plurality of sensors **10**. The generation unit **140** calculates a first latent data column, which is a latent variable data column, from the first data column on the basis of the latent variable model. In the above, the latent variable is not a directly-observed variable (physical quantity), but a variable indirectly estimated through a variation pattern of various data. The latent variable is used for purpose of representing a state or the like behind a sampled physical quantity and is a variable known in the probability model.

For each data output from the plurality of sensors **10**, the generation unit **140** generates a model which represents a probability distribution of latent data corresponding to the data concerned and of estimated data obtained from the latent data. The generation unit **140** generates a probability model for generating the estimated data obtained by estimating outputs from the plurality of sensors **10** after reconstruction from the latent data. The generation unit **140** may supply the generated probability model to the storage unit **130**.

The estimation unit **150** estimates an estimated data column corresponding to the second data column based on the model generated by the generation unit **140** by using regularization in which an error between the second data column and the estimated data column is made sparse. Note here that the term “sparse” means a matrix state in which nonzero components are very few, in other words, in which most components are zero. Therefore, the estimation unit **150** adds a regularization term to a model generated by the generation unit **140** so that most of the components of a difference between the second data column and the estimated data column are zero.

The identification unit **160** identifies a sensor where a change occurred between the first data column and the second data column on the basis of an error between the second data column and the estimated data column. The identification unit **160** identifies, for example, the sensor **10** corresponding to a nonzero component in a difference between the second data column and the estimated data column as a sensor where a change occurred.

Moreover, the identification unit **160** may identify a sensor in which abnormality is detected on the basis of an error between the second data column and the estimated data column. The identification unit **160** may identify the sensor **10** corresponding to the nonzero component as an abnormal sensor in the difference between the second data column and the estimated data column. Alternatively, the identification unit **160** may identify the sensor **10** corresponding to a component having a value equal to or greater than a predetermined value among the nonzero components as an abnormal sensor.

The detection device **100** according to this embodiment identifies an abnormal sensor by generating a probability model based on the first data column output from the plurality of sensors **10** and obtaining estimated data by adding a regularization term in which an error between the second data column and the estimated data based on the second data column is made sparse to the model. The operation of the detection device **100** will be described by using FIG. **2**.

FIG. **2** illustrates an operation flow of the detection device **100** according to this embodiment. The detection device **100** performs the operation flow to identify a small number of abnormal sensors among the plurality of sensors **10** accurately.

First, the first acquisition unit **110** acquires a first data column (S**210**). For example, when the number of the plurality of sensors **10** is D, the first acquisition unit **110** acquires data of N×D columns per row as a first data column $y_n$ (n=1, 2, . . . , N), where $y_n$ is a vector having D elements and a data column represented in D dimensions. The first acquisition unit **110** may receive the vector of the first data column in an array format. Moreover, the storage unit **130** may store the vector of the first data column in an array format.

Subsequently, the second acquisition unit **120** acquires a second data column (S**220**). The second acquisition unit **120** acquires, for example, data of M×N columns per row as a second data column $\eta_m$ (m=1, 2, . . . , M), where $\eta_m$ is a vector having D elements and a data column represented in D dimensions.

Subsequently, the generation unit **140** calculates a first latent data column which is a latent variable data column mapped from the first data column $y_n$ to the latent space on the basis of a latent variable model (S**230**), where the generation unit **140** is allowed to use a known model such as, for example, the graphical Gaussian model (Graphical LASSO), probabilistic PCA (Principal Component Analysis), probabilistic kernel PCA, or Gaussian process latent variable model, as the latent variable model.

The following describes an example that the generation unit **140** of this embodiment uses a known model as a Laplacian eigenmap latent variable model. The generation unit **140** calculates a first latent data column $x_n$ by minimizing the expression of FIG. **1**B on the basis of the depicted model.

In the expression of FIG. **1**B, “argmin f(x)” indicates x in the case where f(x) is minimum, “tr” indicates the sum of diagonal elements (trace), and “subject to g(z)” indicates the meaning of “under the constraint condition g(z).” Moreover, a vector I indicates a unit matrix ($a_{ij}=1$ (i=j), $a_{ij}=0$ (i≠j)) and a vector **1** indicates a row vector in which all elements are 1.

Moreover, the generation unit **140** calculates the first latent data column $x_n$ as a predetermined Q-dimensional data column lower in dimensions than the D dimensions. For example, the generation unit **140** calculates the first latent data column $x_n$ in low dimensions such as three or four dimensions and shows the behaviors of the plurality of sensors **10** in the corresponding three- or four-dimensional latent space. In FIG. **1**B, the matrices L and D are represented by the expressions shown in FIG. **1**C.

In the expressions shown in FIG. **1**C, $w_{n,m}$ is an element of W and “diag(x)” indicates a diagonal matrix. Moreover, σ is a predetermined parameter. For example, when σ increases, the value of $w_{n,m}$, which is an element of the matrix W, approaches zero unless a difference between $y_n$ and $y_m$ increase in response to σ. Moreover, when σ decreases, the value of $w_{n,m}$, which is an element of the matrix W, increases unless the difference between $y_n$ and $y_m$ decrease in response to σ. Specifically, σ serves as a parameter which determines to what extent the difference between $y_n$ and $y_m$ is reflected on the matrix W.

Subsequently, the generation unit **140** generates a model representing a probability distribution of the second latent data column $x_m$ and estimated data obtained from the second latent data on the basis of the first data column $y_n$, the first latent data column $x_n$, and the second data column $\eta_m$ (S**240**). The generation unit **140** generates a joint probability density function $p(\chi_m, v_m|\eta_m, y_n)$ of $\chi_m$ and $v_m$ as represented by the expression shown in FIG. **1**D, where $v_m$ is the estimated data obtained from the second latent data column $\chi_m$.

In the expressions shown in FIG. **1**D, σx and σy are predetermined parameters similarly to σ in FIG. **1**C. The expressions of FIG. **1**D are represented by terms of the norm of $x_n$ and $\chi_m$, the norm of $y_n$ and vm, and the norm of $y_n$ and $\eta_m$, except constants and parameters σx and σy. Specifically, the generation unit **140** generates a model representing a probability distribution where the probability decreases as the difference between the latent data in the second latent data column $\chi_m$ and each latent data of the first latent data column $x_n$ increases, the probability decreases as the difference between the estimated data in the estimated data column $v_m$ and each data of the first data column $y_n$ increases, and the probability decreases as the difference between data in the second data column $\eta_m$ and each data of the first data column $y_n$ increases. In this manner, the generation unit **140** generates a model in which the joint probability density function p of $x_m$ and $v_m$ increases as the values of respective data of $x_n$ and $\chi_m$, $y_n$ and $v_m$, and $y_n$ and $\eta_m$ approach each other.

The estimation unit **150** estimates an estimated data column by reconstruction with sparse regularization on the basis of test data which is an observed value in the known latent variable model as described above (S**250**). For example, the estimation unit **150** calculates the estimated data column $v_m$ by using regularization in which an error between the second data column $\eta_m$ and the estimated data column $v_m$ is concentrated on a data column obtained from particular sensors **10**.

Specifically, the estimation unit **150** calculates the estimated data column $v_m$ by using a regularization term in which the probability decreases as the difference between data in the second data column $\eta_m$ and estimated data in the estimated data column $v_m$ increases. The estimation unit **150** optimizes the joint probability density function p by using the regularization term as described above and calculates the estimated data column $v_m$ corresponding to the second latent data column $\chi_m$, thereby reconstructing a data column substantially coincident with the second data column $\eta_m$.

Note here that the second data column $\eta_m$ is a data column acquired when most sensors **10** normally operate and therefore the estimated data column $v_m$ obtained by the estimation unit **150** substantially coincides with an output data column indicating the behavior of the normal sensor in the N-dimensional superspace. Therefore, the estimation unit **150** calculates the estimated data column $v_m$ so that the data corresponding to an abnormal sensor indicates the behavior different from the behavior of data corresponding to the normal sensor among the data estimated from the second data column $\eta_m$ (in other words, so that the error is large).

Moreover, the estimation unit **150** may calculate the estimated data column by using regularization in which the error between the second data column $\eta_m$ and the estimated data column $v_m$ is concentrated in the time direction with respect to the respective sensors. For example, the estimation unit **150** calculates the estimated data column by using a regularization term in which the probability decreases as the difference between the estimated data in the estimated data column $v_m$ and the estimated data in the estimated data column $v_{m-1}$ which has been estimated before increases. The estimation unit **150** calculates the estimated data column $v_m$ by using the regularization term as described above, thereby reconstructing a data column substantially coincident with the estimated data column $v_{m-1}$ which has been estimated before.

Note here that the second data column $\eta_m$ is a data column acquired when most sensors **10** operate normally and therefore the estimated data column $v_m$ obtained by the estimation unit **150** substantially coincides with output data indicating the behavior of the sensor **10** which operates normally in a temporally stable manner among data of the estimated data column $v_{m-1}$ which has been estimated before. Therefore, the estimation unit **150** calculates the estimated data column $v_m$ so that the data corresponding to an abnormal sensor indicates the behavior different from the behavior of data corresponding to the normal sensor in comparison with the estimated data column $v_{m-1}$ which has been estimated before (in other words, so that the error is large).

Moreover, the estimation unit **150** may calculate the estimated data column by using regularization in which the error between the second data column $\eta_m$ and the estimated data column $v_m$ is concentrated on a data column obtained from particular sensors **10** and the error between the second data column $\eta_m$ and the estimated data column $v_m$ is concentrated in the time direction with respect to the respective sensors. Specifically, the estimation unit **150** calculates the estimated data column $v_m$ by using a regularization term in which the probability decreases as the difference between the data in the second data column $\eta_m$ and the estimated data in the estimated data column $v_m$ increases and the probability decreases as the difference between the estimated data in the estimated data column $v_m$ and the estimated data in the estimated data column $v_{m-1}$ which has been estimated before increases.

As described above, the estimation unit **150** calculates the estimated data column $v_m$ by using the term for regularization. More specifically, as represented by the expression of FIG. **1**E, the estimation unit **150** estimates the second latent data column and the estimated data column which optimize an objective function including a term in which the probability of taking the value of latent data in the second latent data column $\chi_m$ which is a latent variable data column of the second data column $\eta_m$ and the value of the corresponding estimated data in the estimated data column $v_m$ is summed up with respect to the second data column $\eta_m$ and a term for regularization.

The first term of the right side of FIG. **1**E is a term in which the joint probability density function $p(\chi_m, v_m|\eta_m, y_n)$ of $\chi_m$ and $v_m$ illustrated in FIG. **1**D is summed up with respect to the second data column $\eta_m$ which is test data. Moreover, the second term is a term for regularization. The estimation unit **150** uses, for example, a regularization term shown in the expression of FIG. **1**F as a term for regularization.

The first term in the right side of FIG. **1**F is a regularization term in which the probability decreases as the difference between the data in the second data column $\eta_m$ and the estimated data in the estimated data column $v_m$ increases, and the first term is calculated on the basis of the sum of squared values in the respective dimensions. Moreover, the second term is a regularization term in which the probability decreases as the difference between the estimated data in the estimated data column $v_m$ and the estimated data in the estimated data column $v_{m-1}$ which has been estimated before increases, and the second term is calculated on the basis of the sum (L1 norm) of the absolute values of the values in the respective dimensions.

In the above, λ1 and λ2 are parameters for determining the weight of the regularization term to be used. For example, when λ1=1 and λ2=0 are assumed, the estimation unit **150** thereby uses the regularization of the first term of FIG. **1**F. Moreover, when λ1=0 and λ2=1 are assumed, the estimation unit **150** thereby uses regularization of the second term. Furthermore, when λ1≠0 and λ2≠0 are assumed, the estimation unit **150** thereby uses regularization of the first and second terms. λ1 and λ2 may be previously determined according to a purpose or alternatively may be adjusted according to an actual detection result of the detection device **100**.

As described above, the estimation unit **150** is able to calculate the second latent data column $\chi_m'$ and the estimated data column $v_m'$ by optimizing the objective function of FIG. **1**E (in other words, by acquiring $\chi_m$ and $v_m$ which minimize the objective function) by using the regularization terms of FIG. **1**F. Note here that the symbol "'" in the left side of FIG. **1**E indicates a value determined by optimization.

Subsequently, the identification unit **160** identifies a sensor where a change occurred between the first data column $y_n$ and the second data column $\eta_m$ (S**260**). The identification unit **160** identifies, for example, the sensor **10** corresponding to a component in which the score based on the difference between the second data column $\eta_m$ and the estimated data column $v_m'$ represented by the expression of FIG. **1**G is nonzero, as a sensor where a change occurred.

Instead of the score function of FIG. **1**G, the identification unit **160** may use a difference between the second data column $\eta_m$ and the estimated data column $v_m'$ in each dimension d (the maximum value is D) as a score value or may use an expression in which the sum total is calculated with respect to the dimension d in the right side of FIG. **1**G as a score function. The identification unit **160** may identify a sensor **10** where the score is nonzero or equal to or greater than a predetermined value as an abnormal sensor. The estimation unit **150** calculates the estimated data column $v_m'$ in which an error between data corresponding to a normal sensor and data corresponding to an abnormal sensor is made larger on the basis of the second data column $\eta_m$. Therefore, the identification unit **160** is able to identify only the abnormal sensor.

Moreover, even if the number of sensors **10** increases to exceed one hundred, for example, the detection device **100** is able to easily perform processing by increasing the dimension number D of the first data column $y_n$ and the second data column $\eta_m$ correspondingly. Therefore, the detection device **100** is able to determine only the sensors **10** falling in an abnormal signal range even if there are, for example, 100 or more sensors mutually having a complicated correlation in a physical system.

FIG. **3** illustrates an example of a simulation result obtained by the detection device **100** according to this embodiment which calculates the scores of abnormality degrees of the plurality of sensors **10**. Moreover, FIG. **4** illustrates an example of a simulation result obtained by an existing detection device which calculates the scores of abnormality degrees of the sensors. FIGS. **3** and **4** each illustrate a simulation result with respect to outputs of the plurality of sensors which detect the positions of 30 mass points with respect to a physical model with the 30 mass points connected by springs. Since the plurality of mass points are connected by the plurality of springs, the positions of the respective mass points vary in a complicated manner and the corresponding sensors output detection results mutually having a complicated correlation.

The horizontal axis of FIGS. **3** and **4** represents each sensor which detects the corresponding mass point and the vertical axis represents the score value calculated so as to correspond to the sensor. Moreover, FIGS. **3** and **4** each illustrate a result of simulation in which the detection device scores the plurality of sensors in a state where only mass point **3** deviates from the normal behavior.

FIG. **3** illustrates a result of calculation by the detection device **100** according to this embodiment with respect to the scores of abnormality degrees of the plurality of sensors **10**, from which it is understood that only the sensor detecting the mass point **3** outputs a score remarkably high in comparison with other sensors. Meanwhile, FIG. **4** illustrates a result of calculation by the existing detection device with respect to the scores of abnormality degrees of the sensors, which shows a result that, while the score value of the mass point **3** is high, the score values of other mass points having a strong correlation with the mass point **3** are also high.

For example, in the case of generating a prediction model from learning data, the existing detection device learns the model by using a regularization term and detects an abnormal sensor corresponding to test data by using the learned model. Therefore, if one sensor outputs abnormality and sensors having a strong correlation with this sensor also output detection results different from those of the ordinary case and then test data including those detection results are used due to the effect of the sensor concerned, the existing detection device sometimes outputs a high score value for not only the sensor concerned, but also for the sensors having the strong correlation with the sensor, as a result outside the expectation based on the learning data, as illustrated in FIG. **4**.

Meanwhile, the detection device **100** according to this embodiment calculates an estimated data column by using a regularization term in a stage of reconstruction with the test data, instead of the learning stage. Therefore, in the case where one sensor outputs abnormality, the detection device **100** is able to detect that the outputs from other sensors are within the normal operations based on the test data and is able to output the score values of the sensors so that only the score value of the sensor concerned is high as illustrated in FIG. **3**, even if other sensors having a strong correlation with the sensor concerned output detection results different from those of the ordinary case due to the effect of the sensor concerned.

FIG. **5** illustrates a variation of the detection device **100** according to this embodiment along with the plurality of sensors **10**. The same reference numerals are used for the units performing substantially the same operations as those of the detection device **100** according to the embodiment illustrated in FIG. **1**A in the detection device **100** of the variation and the description thereof is omitted here. The detection device **100** according to the variation further includes an adjustment unit **210**.

The adjustment unit **210** is connected to the storage unit **130**, the estimation unit **150**, and the identification unit **160** and adjusts the weights λ1 and λ2 of the regularization used by the estimation unit **150** so that a sensor **10** identified by the identification unit **160** coincides with a known sensor **10** in which a change occurred. In this case, the second acquisition unit **120** acquires a second data column $\eta_m$ in which a sensor where a change occurred is known for the first data column $y_n$. Furthermore, the detection device **100** identifies an abnormal sensor by performing the operation flow of FIG. **2** on the basis of the first data column $y_n$ and the second data column $\eta_m$ and thereafter the adjustment unit **210** adjusts the values of λ1 and λ2 so that the identification result of the identification unit **160** corresponds to the change information of the known sensor.

The adjustment unit **210** may update the values of λ1 and λ2 to perform loop processing of repeating the adjustment of the values of λ1 and λ2 a plurality of times. In this manner, the detection device **100** according to the variation is able to adjust the weights of the regularization on the basis of an actual identification result and therefore is able to score the abnormality degrees of the sensors more accurately.

In the variation of the detection device **100** according to the embodiment, it has been described that the adjustment unit **210** adjusts the values of the weights λ1 and λ2 of the regularization. Alternatively or in addition to this, the adjustment unit **210** may adjust the values of the parameters σ, σx, and σy. This enables the detection device **100** to increase the accuracy of the scores of the sensors **10** by easily performing the parameter adjustment.

FIG. **6** illustrates an example of a hardware configuration of a computer **1900** which functions as the detection device **100** according to the embodiment. The computer **1900** according to the embodiment includes a CPU peripheral unit, an input/output unit, and a legacy input/output unit. The CPU peripheral unit includes a CPU **2000**, a RAM **2020**, and a graphics controller **2075**, all of which are mutually connected to one another via a host controller **2082**. The CPU peripheral unit also includes a display device **2080**. The input/output unit includes a communication interface **2030**, a hard disk drive **2040**, and a DVD drive **2060**, all of which are connected to the host controller **2082** via an input/output controller **2084**. The legacy input/output unit includes a ROM **2010**, a flexible disk drive **2050**, and an input/output chip **2070**, all of which are connected to the input/output controller **2084**.

The host controller **2082** mutually connects the RAM **2020** to the CPU **2000** and the graphics controller **2075**, both of which access the RAM **2020** at a high transfer rate. The CPU **2000** operates on the basis of a program stored in the ROM **2010** and the RAM **2020**, and controls each of the components. The graphics controller **2075** acquires image data generated by the CPU **2000** or the like in a frame buffer provided in the RAM **2020**, and causes the display device **2080** to display the acquired image data. In place of this, the graphics controller **2075** may internally include a frame buffer in which the image data generated by the CPU **2000** or the like is stored.

The input/output controller **2084** connects the host controller **2082** to the communication interface **2030**, the hard disk drive **2040**, and the DVD drive **2060**, all of which are relatively high-speed input/output devices. The communication interface **2030** communicates with another device via a network. The hard disk drive **2040** stores, therein, a program and data to be used by the CPU **2000** in the computer **1900**. The DVD drive **2060** reads a program or data from a DVD-ROM **2095** and provides the read program or data to the hard disk drive **2040** via the RAM **2020**.

In addition, the input/output controller **2084** is connected to relatively low-speed input/output devices such as the ROM **2010**, the flexible disk drive **2050**, and the input/output chip **2070**. The ROM **2010** stores a program such as a boot program executed at a start-up time of the computer **1900** and/or a program depending on hardware of the computer **1900** or the like. The flexible disk drive **2050** reads a program or data from a flexible disk **2090**, and provides the read program or data to the hard disk drive **2040** via the RAM **2020**. The input/output chip **2070** connects the flexible disk drive **2050** to the input/output controller **2084** and also connects various kinds of input/output devices to the input/output controller **2084** through a parallel port, a serial port, a keyboard port, a mouse port, and the like, for example.

A program to be provided to the hard disk drive **2040** via the RAM **2020** is provided by a user with the program stored in a recording medium such as the flexible disk **2090**, the DVD-ROM **2095**, or an IC card. The program is read from the storage medium, then installed in the hard disk drive **2040** in the computer **1900** via the RAM **2020**, and executed by the CPU **2000**.

The program is installed in the computer **1900** to cause the computer **1900** to function as the first acquisition unit **110**, the second acquisition unit **120**, the storage unit **130**, the generation unit **140**, the estimation unit **150**, the identification unit **160**, and the adjustment unit **210**.

Information processes written in the programs are read by the computer **1900** and thereby functions as the first acquisition unit **110**, the second acquisition unit **120**, the storage unit **130**, the generation unit **140**, the estimation unit **150**, the identification unit **160**, and the adjustment unit **210**, all of which are specific means resulting from cooperation of software and the aforementioned various types of hardware resources. Then, the detection device **100** specific to an intended purpose is built up by performing computation or processing of information in accordance with the intended purpose of the computer **1900** in this embodiment by use of such specific means.

In a case where communications between the computer **1900** and an external device or the like are performed, for example, the CPU **2000** executes a communication program loaded on the RAM **2020** and instructs the communication interface **2030** on the basis of processing contents described in the communication program to perform communication processing. Upon receipt of the control from the CPU **2000**, the communication interface **2030** reads transmission data stored in a transmission buffer region or the like provided in a storage device such as the RAM **2020**, the hard disk drive **2040**, the flexible disk **2090**, or the DVD-ROM **2095** and then transmits the data to a network or writes reception data received from the network into a receiving buffer region or the like provided on a storage device. As described above, the communication interface **2030** is allowed to transfer transmission and reception data between itself and a storage device by a direct memory access (DMA) scheme. Instead of this, the CPU **2000** is also allowed to read data from a storage device or a communication interface **2030** of a transfer source and then to transfer transmission and reception data by writing the data into a communication interface **2030** or a storage device of a transfer destination.

In addition, the CPU **2000** causes all or a required portion of data to be read from a file or a database stored in an external storage device such as the hard disk drive **2040**, the DVD drive **2060** (DVD-ROM **2095**), the flexible disk drive **2050** (flexible disk **2090**) or the like into the RAM **2020** by DMA transfer or the like, and then performs various kinds of processing for the data in the RAM **2020**. Then, the CPU **2000** writes the processed data back in the external storage device by DMA transfer or the like. In such processing, since the RAM **2020** can be considered as a device in which the contents of an external storage device are stored temporarily, the RAM **2020** and an external storage device or the like are collectively termed as a memory, a storage unit, a storage device, or the like in this embodiment. Various types of information including various types of programs, data, tables, databases, and the like in this embodiment are stored in such a storage device and are handled as an information processing target. It should be noted that the CPU **2000** is allowed to retain a part of data in the RAM **2020** in a cache memory and then to read and write the data in the cache memory. In this case as well, since the cache memory partially shares the function of the RAM **2020**, the cache memory is considered to be included in the RAM **2020**, a memory and/or a storage device except for a case where the cache memory needs to be distinguished from the RAM **2020**, the memory, and/or the storage device in this embodiment.

In addition, the CPU **2000** performs, on the data read from the RAM **2020**, various types of processing being specified by a sequence of instructions of the program and including various types of computations, information processing, conditional judgment, information retrieval and replacement and the like described in this embodiment, and writes the processed data back in the RAM **2020**. In a case where the CPU **2000** performs conditional judgment, for example, the CPU **2000** determines by comparing a variable with the other variable or constant whether or not each of various types of variables indicated in the present embodiment satisfies a condition that the variable is larger, smaller, not less, not greater, equal, or the like. In the case where the condition is satisfied (or the condition is not satisfied), the processing of the CPU **2000** branches to a different instruction sequence or calls a subroutine.

In addition, the CPU **2000** is capable of searching for information stored in a file, a database, or the like in a storage device. For example, in a case where multiple entries having attribute values of a first attribute respectively associated with attribute values of a second attribute are stored in a storage device, the CPU **2000** searches the multiple entries stored in the storage device for an entry whose attribute value of the first attribute matches a specified condition. Then, the CPU **2000** reads an attribute value of the second attribute stored in the entry, and thereby, obtains the attribute value of the second attribute that satisfies the predetermined condition and that is associated with the first attribute.

The programs or modules described above may be stored as a computer program product on a computer readable storage medium such as an external recording medium. As the recording medium, any one of the following media may be used: an optical recording medium such as a DVD, Blu-ray®, or a CD; a magneto-optic recording medium such as an MO; a tape medium; and a semiconductor memory such as an IC card, in addition to the flexible disk **2090** and the DVD-ROM **2095**. Alternatively, the program may be provided to the computer **1900** via a network, by using, as a recording medium, a storage device such as a hard disk or a RAM provided in a server system connected to a private communication network or the Internet.

The present invention has been described hereinabove with reference to preferred embodiments. The technical scope of the present invention, however, is not limited to the above-described embodiments only. It is apparent to one skilled in the art that various modifications or improvements may be made to the above-described embodiments. Accordingly, it is also apparent from the scope of the claims that the embodiments with such modifications or improvements added thereto can be included in the technical scope of the invention.

It should be noted that the operations, procedures, steps, and stages of each process performed by an apparatus, system, program, and method shown in the claims, embodiments, or diagrams can be performed in any order as long as the order is not indicated by "prior to," "before," or the like and as long as the output from a previous process is not used in a later process. Even if the operation flow is described using phrases such as "first" or "next" in the claims, embodiments, or diagrams, it does not necessarily mean that the process must be performed in this order.

It should be noted that the apparatuses disclosed herein may be integrated with additional circuitry within integrated circuit chips. The resulting integrated circuit chips can be distributed by the fabricator in raw wafer form (that is, as a single wafer that has multiple unpackaged chips), as a bare die, or in a packaged form. In the latter case, the chip is mounted in a single chip package (such as a plastic carrier, with leads that are affixed to a motherboard or other higher level carrier) or in a multichip package (such as a ceramic carrier that has either or both surface interconnections or buried interconnections). In any case, the chip is then integrated with other chips, discrete circuit elements, and/or other signal processing devices as part of either (a) an intermediate product, such as a motherboard, or (b) an end product. The end product can be any product that includes integrated circuit chips, ranging from toys and other low-end applications to advanced computer products having a display, a keyboard or other input device, and a central processor.

It should be noted that this description is not intended to limit the invention. On the contrary, the embodiments presented are intended to cover some of the alternatives, modifications, and equivalents, which are included in the spirit and scope of the invention as defined by the appended claims. Further, in the detailed description of the disclosed embodiments, numerous specific details are set forth in order to provide a comprehensive understanding of the claimed invention. However, one skilled in the art would understand that various embodiments may be practiced without such specific details.

Although the features and elements of the embodiments disclosed herein are described in particular combinations, each feature or element can be used alone without the other features and elements of the embodiments or in various combinations with or without other features and elements disclosed herein.

This written description uses examples of the subject matter disclosed to enable any person skilled in the art to practice the same, including making and using any devices or systems and performing any incorporated methods. The patentable scope of the subject matter is defined by the claims, and may include other examples that occur to those skilled in the art. Such other examples are intended to be within the scope of the claims.

What is claimed is:

**1**. An apparatus for identifying abnormal output by a sensor comprising:

a memory and a processor configured to:

measure at least one respective first output for each respective sensor of a plurality of sensors, wherein the plurality of sensors comprise at least one temperature sensor;

acquire a first data column based on the first outputs;

generate a Laplacian eigenmap latent variable model for estimating data from the plurality of sensors on the basis of the first data column;

measure at least one respective second output for each respective sensor of the plurality of sensors;

acquire a second data column based on the second outputs;

obtain an estimated data column corresponding to the second data column based on the Laplacian eigenmap latent variable model by using regularization for making an error between the second data column and the estimated data column sparse;

identify a sensor of the plurality of sensors in which a change occurred between the first data column and the second data column on the basis of the error between the second data column and the estimated data column, wherein the error between the second data column and the estimated data column for the sensor comprises a non-zero score; and

output the non-zero score and an identification of the sensor in which the change occurred.

**2**. The apparatus of claim **1**, wherein the processor configured to obtain an estimated data column is further configured to calculate the estimated data column by using regularization in which the error between the second data column and the estimated data column is concentrated on a data column from particular sensors.

**3**. The apparatus of claim **2**, wherein the processor configured to obtain an estimated data column is further configured to calculate the estimated data column by using regularization in which the error between the second data column and the estimated data column is concentrated on a data column from particular sensors and the error between the second data column and the estimated data column is concentrated in a time direction with respect to the particular sensors.

**4**. The apparatus of claim **1**, wherein the processor configured to generate a Laplacian eigenmap latent variable model is further configured to calculate a first latent data column which is a latent variable data column from the first data column and generate the Laplacian eigenmap latent variable model, the Laplacian eigenmap latent variable model representing a probability distribution of latent data corresponding to respective data output from the plurality of sensors and of estimated data obtained from the latent data for the respective data, and the processor is further configured to estimate a second latent data column and the estimated data column which optimizes an objective function including a term in which the probability of taking the value of latent data in a second latent data column which is a latent variable data column of the second data column and the value of the corresponding estimated data in the estimated data column is summed up with respect to the second data column and a term for regularization.

**5**. The apparatus of claim **4**, wherein the processor configured to generate a Laplacian eigenmap latent variable model is further configured to generate the Laplacian eigenmap latent variable model such that the Laplacian eigenmap latent variable model represents a probability distribution wherein the probability decreases as a difference between the latent data in the second latent data column and each latent data of the first latent data column increases, wherein the probability decreases as a difference between the estimated data in the estimated data column and each data of the first data column increases, and wherein the probability decreases as a difference between the data in the second data column and each data of the first data column increases.

**6**. The apparatus of claim **1**, wherein the processor is further configured to acquire the second data column in which a sensor where a change occurred is known for the first data column, and the processor is further configured to adjust weights of regularization used by the estimation unit so that an identified sensor coincides with the known sensor in which the change occurred.

**7**. The apparatus of claim **1**, wherein the processor is further configured to acquire the first data column for learning indicating a normal behavior of a measuring object, the processor is further configured to acquire the second data column detected from the measuring object, and the processor is further configured to identify a sensor in which abnormality is detected on the basis of an error between the second data column and the estimated data column.

**8**. A method for identifying abnormal output by a sensor comprising:

measuring at least one respective first output for each respective sensor of a plurality of sensors, wherein the plurality of sensors comprise at least one temperature sensor;

acquiring a first data column based on the first outputs;

generating a Laplacian eigenmap latent variable model for estimating data from the plurality of sensors on the basis of the first data column;

measuring at least one respective second output for each respective sensor of the plurality of sensors;

acquiring a second data column based on the second outputs;

obtaining an estimated data column corresponding to the second data column based on the Laplacian eigenmap latent variable model by using regularization for making an error between the second data column and the estimated data column sparse;

identifying a sensor of the plurality of sensors in which a change occurred between the first data column and the second data column on the basis of the error between the second data column and the estimated data column, wherein the error between the second data column and the estimated data column for the sensor comprises a non-zero score; and

outputting the non-zero score and an identification of the sensor in which the change occurred.

**9**. The method of claim **8**, wherein the estimated data column is calculated by using regularization in which the error between the second data column and the estimated data column is concentrated on a data column from particular sensors.

**10**. The method of claim **9**, wherein the estimated data column is calculated by using regularization in which the error between the second data column and the estimated data column is concentrated on a data column from particular sensors and the error between the second data column and the estimated data column is concentrated in a time direction with respect to the respective sensors.

**11**. The method of claim **8**, further comprising:

calculating a first latent data column which is a latent variable data column from the first data column and generating the Laplacian eigenmap latent variable model representing a probability distribution of latent data corresponding to respective data output from the plurality of sensors and of estimated data obtained from the latent data for the respective data; and

estimating a second latent data column and the estimated data column which optimize an objective function including a term in which the probability of taking the value of latent data in the second latent data column which is a latent variable data column of the second data column and the value of the corresponding estimated data in the estimated data column is summed up with respect to the second data column and a term for regularization.

**12**. The method of claim **11**, further comprising generating the Laplacian eigenmap latent variable model representing a probability distribution where the probability decreases as a difference between the latent data in the second latent data column and each latent data of the first latent data column increases, wherein the probability decreases as a difference between the estimated data in the estimated data column and each data of the first data column increases, and wherein the probability decreases as a difference between the data in the second data column and each data of the first data column increases.

**13**. The method of claim **8**, further comprising:

acquiring the second data column in which a sensor where a change occurred is known for the first data column; and

adjusting weights of regularization so that an identified sensor coincides with the known sensor in which the change occurred.

**14**. The method of claim **8**, further comprising:

acquiring the first data column for learning indicating a normal behavior of a measuring object;

acquiring the second data column detected from the measuring object; and

identifying a sensor in which abnormality is detected on the basis of an error between the second data column and the estimated data column.

**15**. A computer program product for identifying abnormal output by a sensor comprising one or more non-transitory computer readable storage media and program instructions stored on the one or more non-transitory computer readable storage media, the program instructions comprising instructions to:

measure at least one respective first output for each respective sensor of a plurality of sensors, wherein the plurality of sensors comprise at least one temperature sensor;

acquire a first data column based on the first outputs;

generate a Laplacian eigenmap latent variable model for estimating data from the plurality of sensors on the basis of the first data column;

measure at least one respective second output for each respective sensor of the plurality of sensors;

acquire a second data column based on the second outputs;

obtain an estimated data column corresponding to the second data column based on the Laplacian eigenmap latent variable model by using regularization for making an error between the second data column and the estimated data column sparse;

identify a sensor of the plurality of sensors in which a change occurred between the first data column and the second data column on the basis of the error between the second data column and the estimated data column, wherein the error between the second data column and the estimated data column for the sensor comprises a non-zero score; and

output the non-zero score and an identification of the sensor in which the change occurred.

**16**. The computer program product of claim **15**, wherein the estimated data column is calculated by using regularization in which the error between the second data column and the estimated data column is concentrated on a data column from particular sensors.

**17**. The computer program product of claim **16**, wherein the estimated data column is calculated by using regularization in which the error between the second data column and the estimated data column is concentrated on a data column from particular sensors and the error between the second data column and the estimated data column is concentrated in a time direction with respect to the respective sensors.

**18**. The computer program product of claim **15**, wherein the program instructions comprise instructions to:

calculate a first latent data column which is a latent variable data column from the first data column and generating the Laplacian eigenmap latent variable model representing a probability distribution of latent data corresponding to respective data output from the plurality of sensors and of estimated data obtained from the latent data for the respective data; and

estimate the second latent data column and the estimated data column which optimize an objective function including a term in which the probability of taking the value of latent data in the second latent data column which is a latent variable data column of the second data column and the value of the corresponding estimated data in the estimated data column is summed up with respect to the second data column and a term for regularization.

**19**. The computer program product of claim **18**, wherein the program instructions comprise instructions to generate the Laplacian eigenmap latent variable model representing a probability distribution wherein the probability decreases as a difference between the latent data in the second latent data column and each latent data of the first latent data column increases, wherein the probability decreases as a difference between the estimated data in the estimated data column and each data of the first data column increases, and wherein the probability decreases as a difference between the data in the second data column and each data of the first data column increases.

**20**. The computer program product of claim **15**, wherein the program instructions comprise instructions to:

acquire the second data column in which a sensor where a change occurred is known for the first data column; and

adjust weights of regularization so that an identified sensor coincides with the known sensor in which the change occurred.

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